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Detection and Classification from Hyperspectral Imagery Using the Normal Compositional Model

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ASAP 2003

11-13 March 2003

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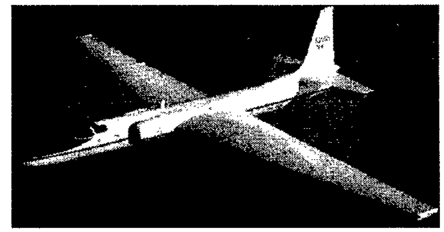
Outline

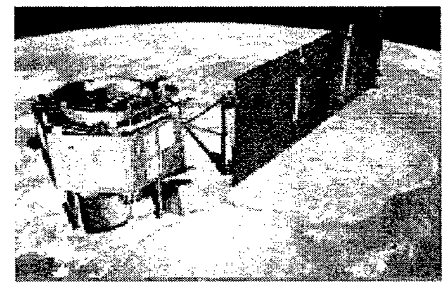
- Hyperspectral Imaging (HSI) aka Imaging Spectrometry
- Descriptive models of HSI
- The Normal Compositional Model
- Applications
- Summary
- Future Work

Hyperspectral Imaging or Imaging Spectrometry

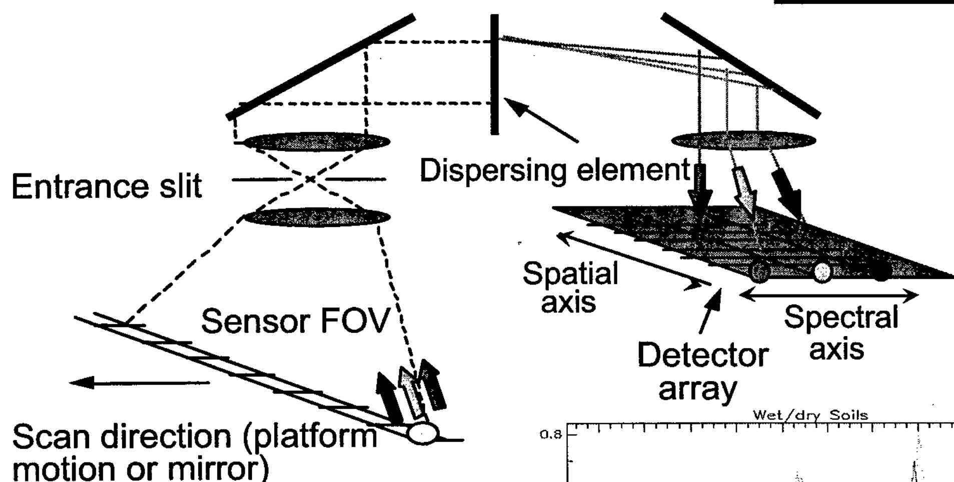
NASA: ER2 AVIRIS



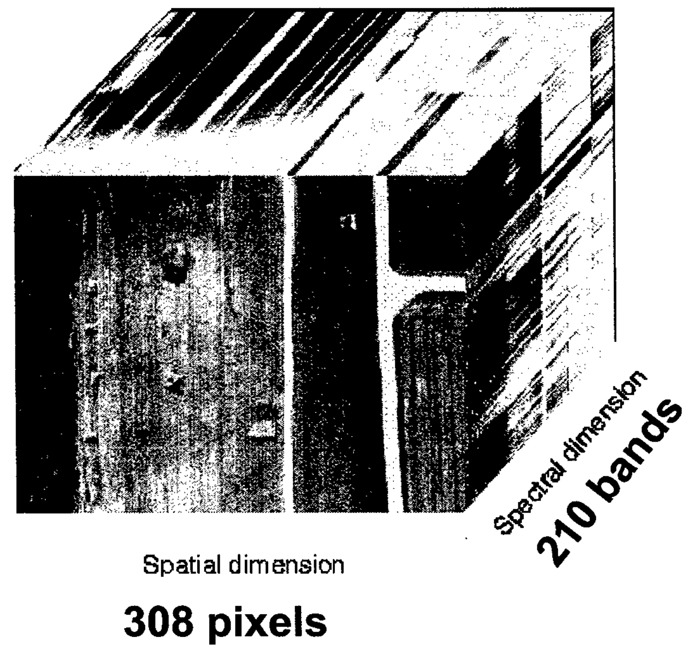
NASA: E01 HYPERION



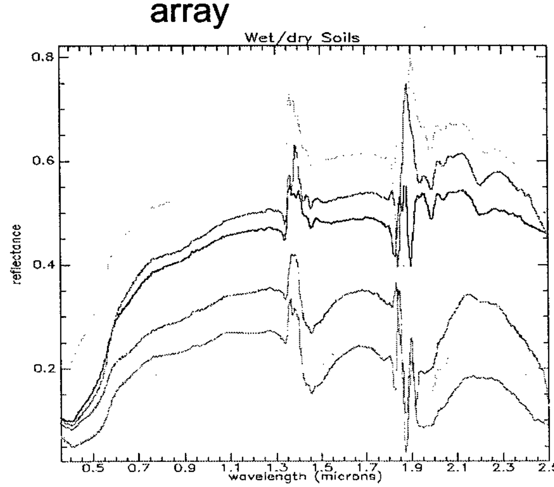
Hyperspectral Imager



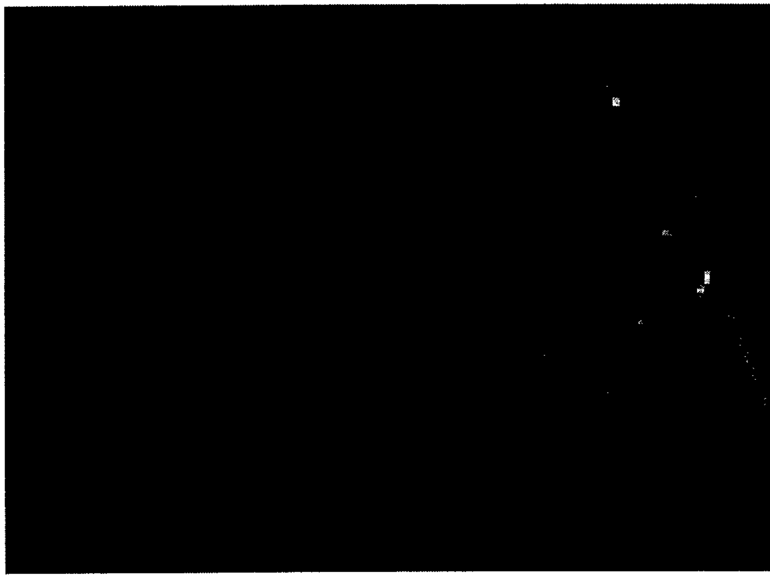
NRL: HYDICE 0.4-2.4 nm



reflectance spectra of various soils



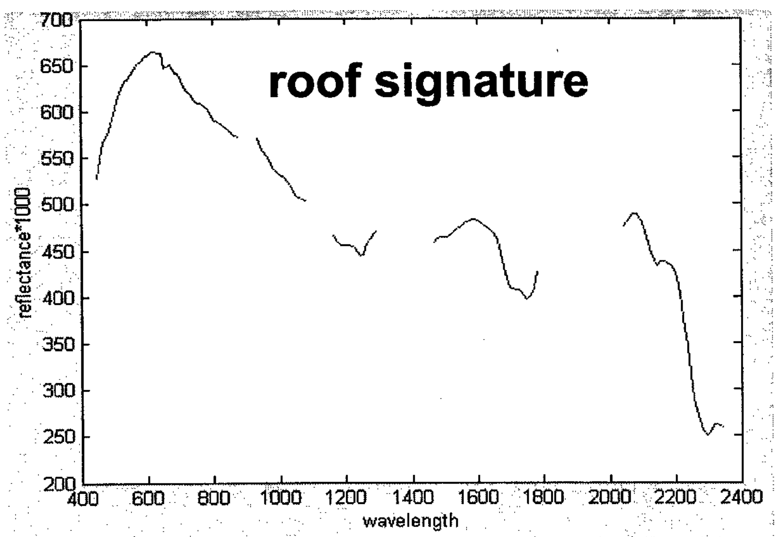
Detection of a Known Target

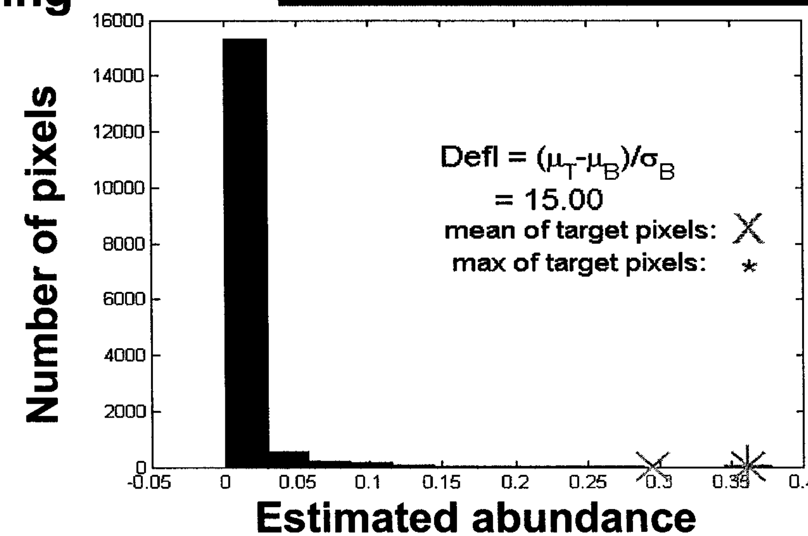


RGB: HYPERION (30m GSD, 195 bands down sampled to 47, 400-2400 nm, modeled with 10 background and 1 target classes)

subpixel building

Detection statistic (LMM target abundance)



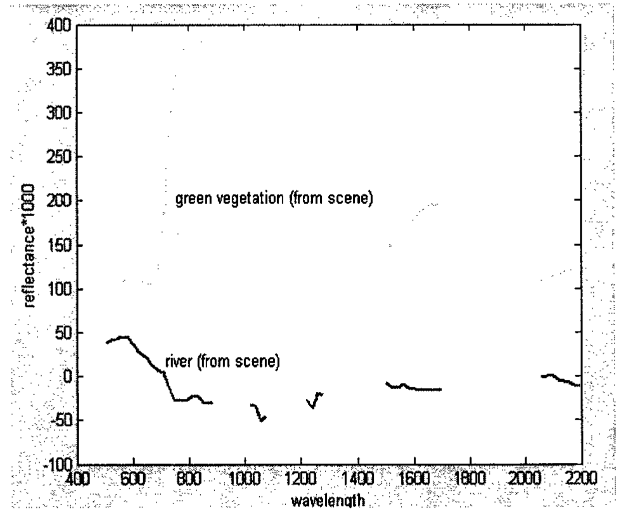


HSI: Blind Unmixing

- Estimate class spectra from scene w/o library
- Estimate abundance of each material at each pixel

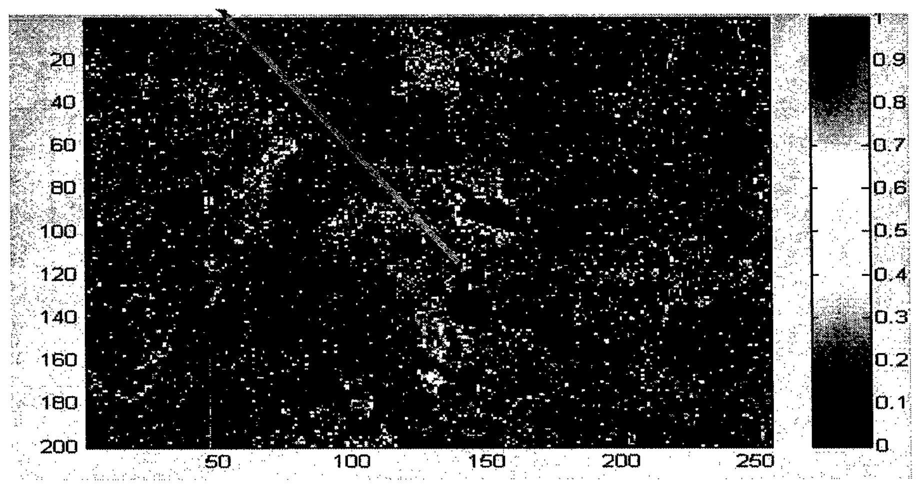
HYPERION RGB: 11 classes

Example class spectra



Abundance maps: water

Green vegetation

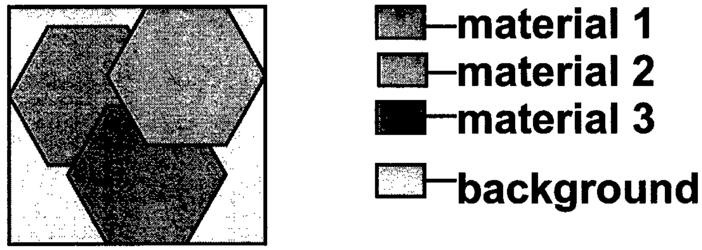


Outline

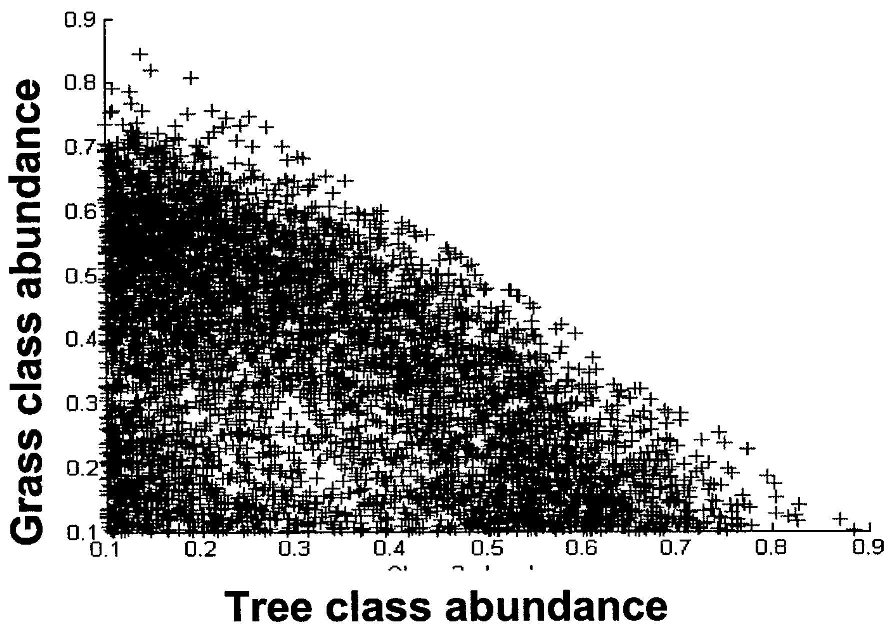
- **Hyperspectral Imaging (HSI) aka Imaging Spectrometry**
- **Descriptive models of HSI**
  - Characteristics of HSI
  - Modeling intra-class variability
  - Common approaches to modeling HSI
- **Applications**
- **Summary**
- **Conclusions**

Important Characteristics of HSI

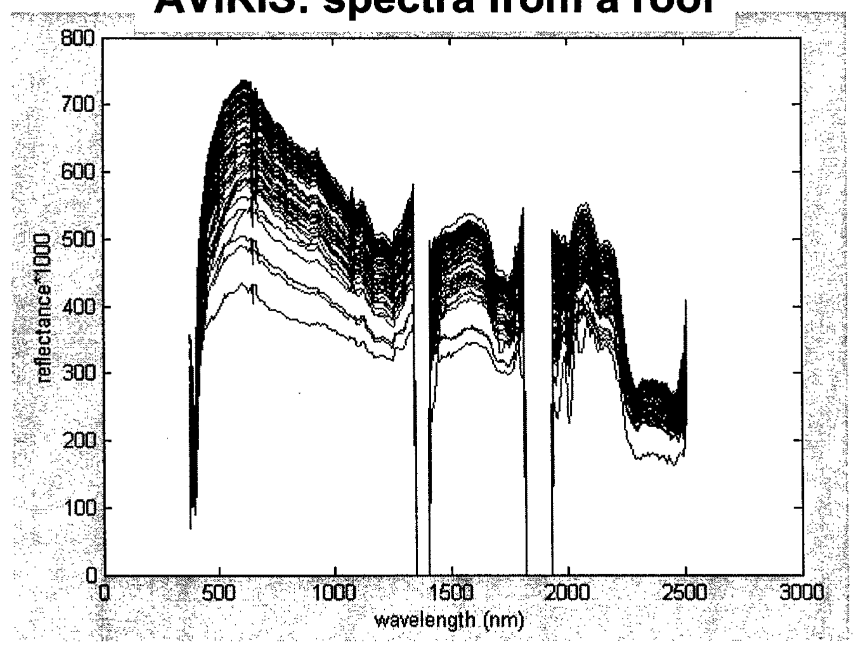
Different materials occlude each other



Pixels are generally mixtures
(ARMY Night Vision Lab: NVIS- forest)



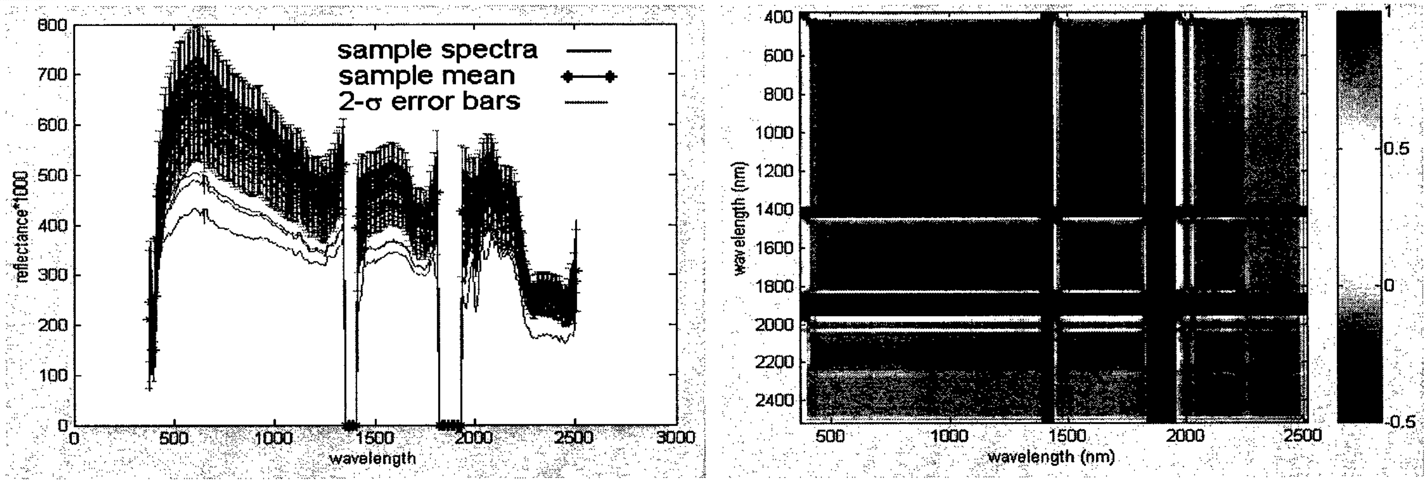
AVIRIS: spectra from a roof



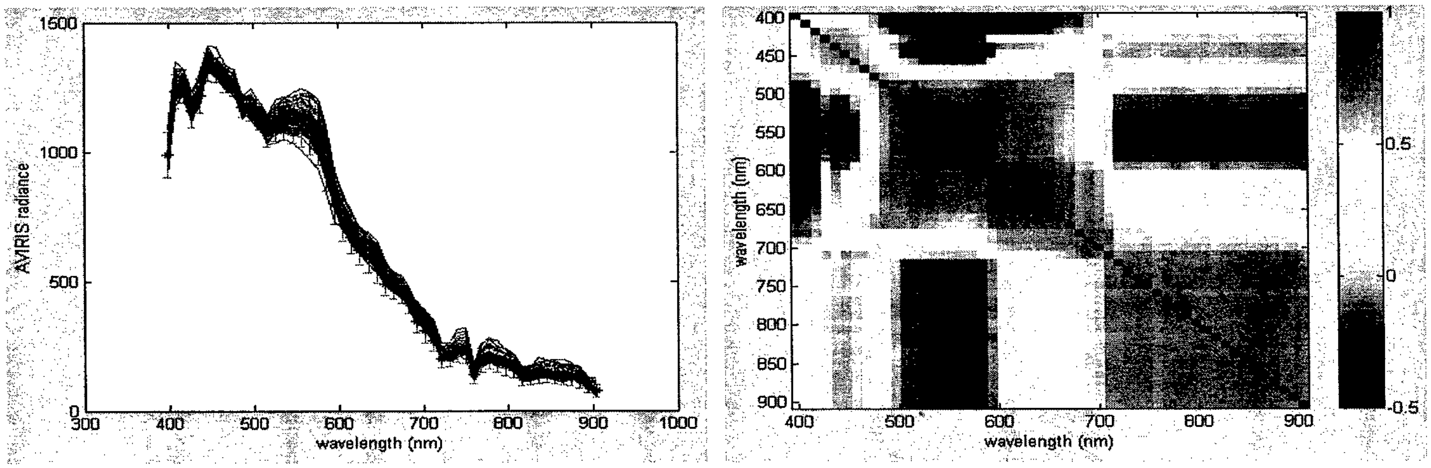
Materials not well modeled by a single spectrum

Random Models of Spectral Variability: First and Second Order Statistics

AVIRIS (400-2400 nm) Southern CA multiple roof reflectance spectra



AVIRIS (400-900 nm) Tampa Bay radiance spectra identified with phytoplankton class



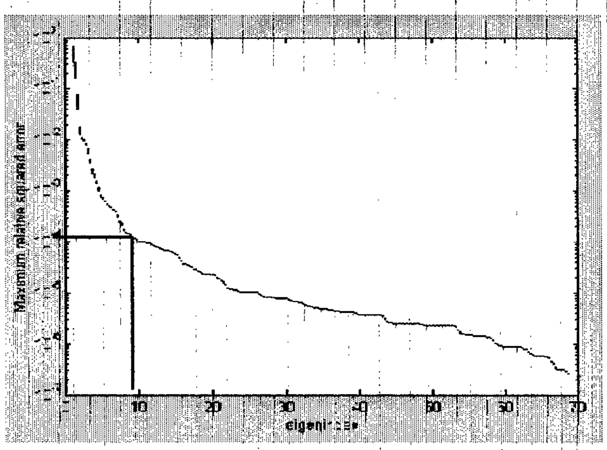
- Correlation matrix is independent of radiance-to-reflectance transformation
- Correlation matrix is class dependent
- Significance of modeling variability judged by impact on performance

Subspace Models of Spectral Variability

- **Subspace model:**
  - Define a low-dimensional subspace such that target signatures may be replaced, with bounded error, by projection onto subspace
- **Eigenvector construction**
  - Given observations $\{x_i, \ldots, x_m\} \subset R^n$ define $T = \sum_{i=1}^{m} x_i \cdot x_i^* = UDU'$
  - Relative magnitude of the error vector obtained by ignoring the last N-p eigenvectors, where N=rank(T), is

$$err^2(p) = \max_i \frac{\sum_{j=p+1}^{N} \left|u_j^* x_i\right|^2}{\left|x_i\right|^2}$$

  - Applied to the roof data above

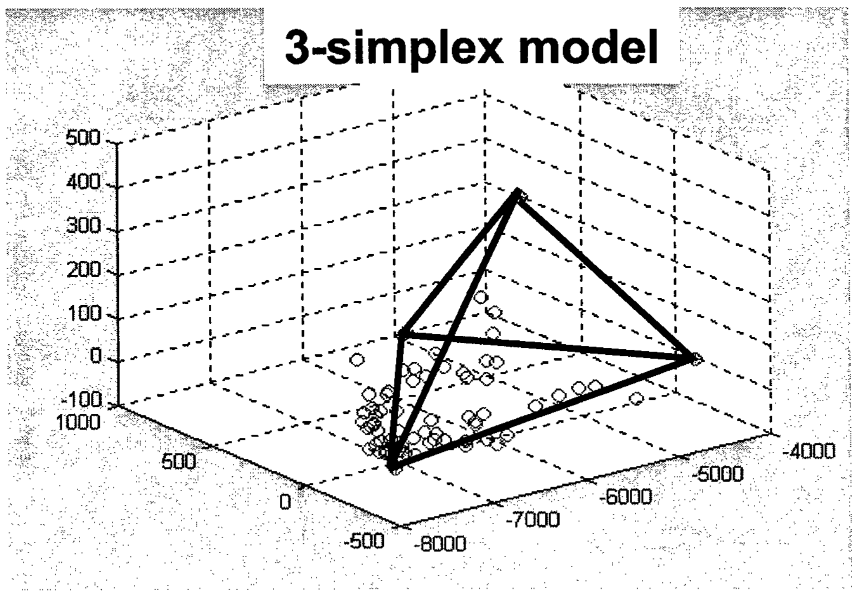


Dimension (p)	$err^2(p)$
5	0.0009
10	0.0001

Convex Models of Spectral Variability

- Find simplex such that every target is approximately represented as a convex mixture (linear combination such that coefficients are positive and sum to 1) of the vertices
- Construction of maximum volume inscribed n-simplex
  - Project samples onto first n eigenvectors of correlation matrix
  - Select n+1 affine independent samples
  - apply determinant update equations to maximize volume

AVIRIS
roof data



* Endmember

o Projected data

Common Approaches to Modeling HSI

- **Local Normal model**

$$x \in Neigh(z) \Rightarrow x \sim N(\mu_z, \Gamma_z)$$

- **Normal mixture model**

$$x \sim \sum_{j=1}^{m} \rho_j N(\mu_j, \Gamma_j); \rho_j \geq 0 \text{ and } \sum_{j=1}^{m} \rho_j = 1$$

- **Subspace models (linear)**

$$x_i = A\alpha_i + n, n \sim N(\mu, \Gamma)$$

- **Linear mixture models (convex)**

$$x_i = \sum_{j=1}^{m} a_{ij} s_j + n; a_{ij} \geq 0 \text{ and} \sum_{j=1}^{m} a_{ij} = 1; n \sim N(\mu, \Gamma)$$

- **None of these models accounts for 1) occlusion, 2) intra-class variability, and 3) subpixel mixing**

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Normal Compositional Model

- **Observation** $\vec{x}_i$ **is modeled as**

$$\vec{x}_i = \vec{e}_0 + \sum_{j=1}^{m} a_{ij}\vec{e}_j \text{ such that } \vec{e}_0 \sim N(\vec{\mu}_0, \Gamma_0) \text{ and } \vec{e}_j \sim N(\vec{\mu}_j, \Gamma_j)$$

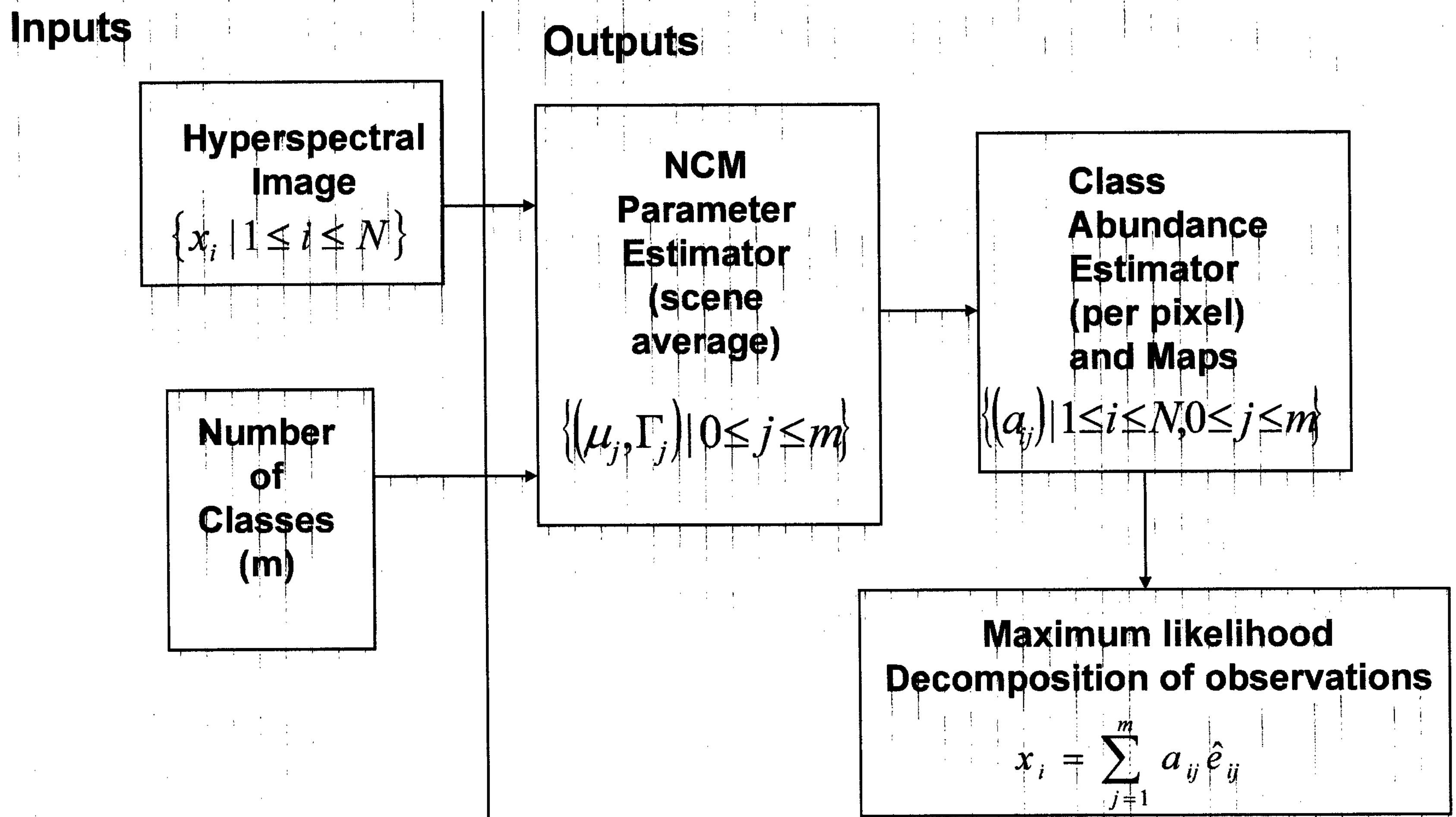
subject to constraints

$$0 \le a_{ij} \text{ for } j \le r, \text{ and either } \sum_{j=1}^{r} a_{ij} = 1 \text{ or } \sum_{j=1}^{r} a_{ij} \le 1;\ \mathrm{r} \le \mathrm{m}.$$

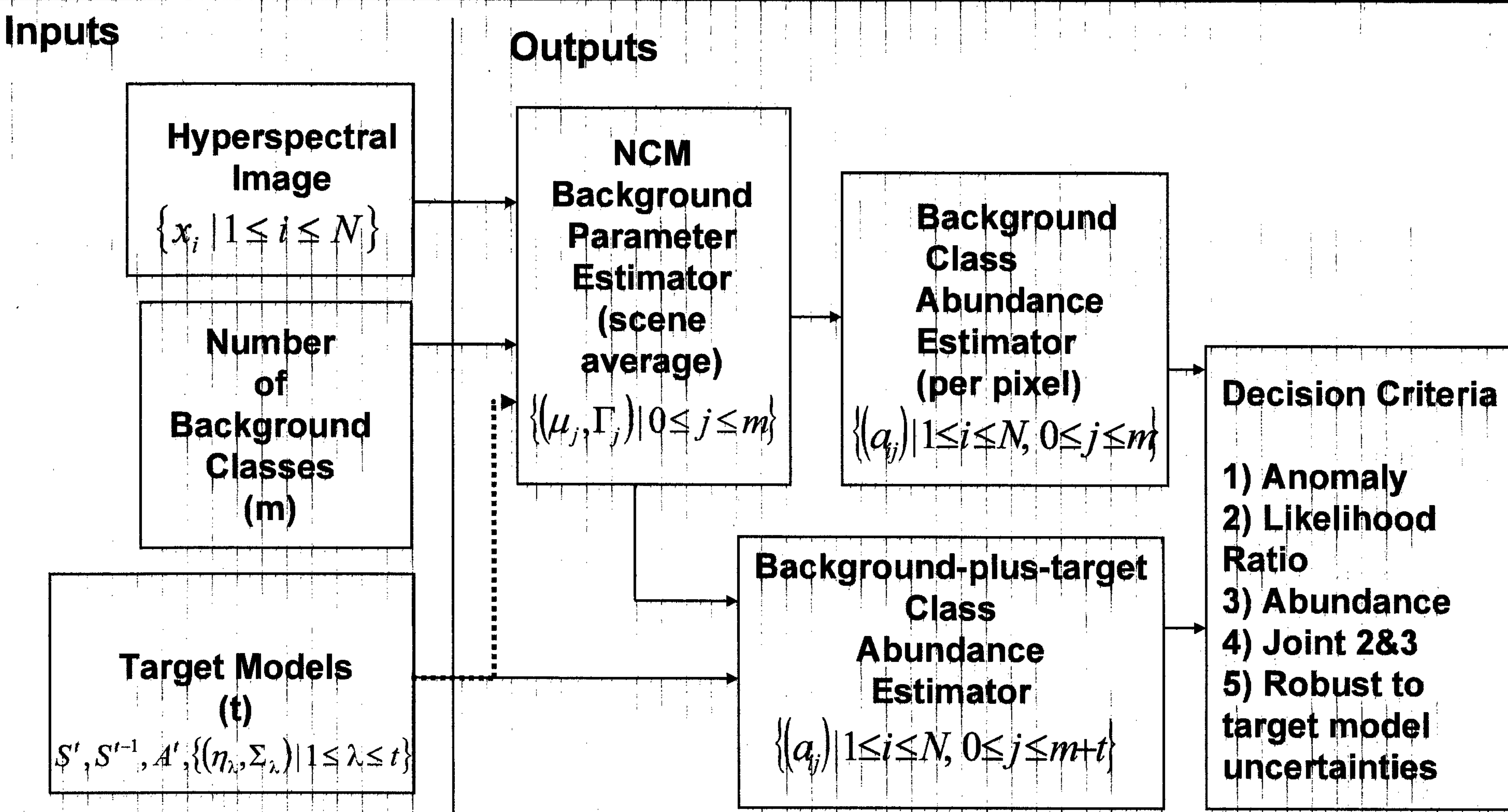
- **Features:**
  - **Models subpixel mixing and random variation within a class**
  - **Class parameters** $\{(\mu_j, \Gamma_j) \mid 0 \le j \le m\}$ **estimated as scene wide aggregates**
  - **Estimates of class parameters converge under appropriate hypotheses to true values**
  - **Abundance values** $\{a_{ij} \mid 1 \le j \le m, 1 \le i \le N\}$ **estimated at every pixel**
  - **Additive components, e.g. noise and path radiance**
  - **Accommodates (fat) subspace as well as (fat) simplex models.**

- **Special Cases: Linear mixture, Gaussian mixture and subspace models**

NCM Blind Unmixing



NCM Detection



Estimation of NCM Parameters: Nested Expectation Maximization

- **Complete Likelihood function:**
  - N observations x_i and abundance vectors $\alpha_i = (a_{i1}, \ldots, a_{im})$

$$p\left(x_1, \ldots, x_N, a_{11}, \ldots a_{1m}, \ldots, a_{N1}, \ldots, a_{Nm} \mid \{(\mu_j, \Gamma_j)\}\right) = \prod_{i=1}^{N} N\left(x_i; \mu(\alpha_i) + \mu_0, \Gamma(\alpha_i) + \Gamma_0\right) p(\alpha_i)$$

- **where** $\mu(\alpha_i) = \sum_{j=1}^{m} a_{ij}\mu_j$ and $\Gamma(\alpha_i) = \sum_{j=1}^{m} a_{ij}{}^2\Gamma_j$

- **Abundance values are hidden parameters**

  0. Initialize class parameters $\{(\mu_j{}^0, \Gamma_j{}^0) \mid 0 \le j \le m\}$
     - Linear mixture model techniques to identify initial endmembers (HSI)
     - Vertices of convex hull (low dimensional, e.g., multispectral, data)
  1. Sample hidden parameters $\{a_{ij}{}^r \mid 0 \le j \le m, 1 \le i \le N\}$
     - Optimization of likelihood function (currently)
     - Monte Carlo Markov Chain (in progress)
  2. Optimize class parameters for given values of hidden parameters
     - Expectation-Maximization Algorithm $\{(\mu_j{}^{\lambda+1}, \Gamma_j{}^{\lambda}) \mid 0 \le j \le m\}$
  3. Repeat 1 and 2 until a convergence criterion is met

Updating Class Parameters Using Expectation Maximization

- **Class parameters after iteration ℓ**

$$\Omega^{\ell} = \left\{ \left(\mu_j^{\ell}, \Gamma_j^{\ell}\right) \mid 0 \le j \le m \right\}$$

- **Class mean update:**

$$\mu_k^{\ell+1} = \frac{1}{N} \sum_{i=1}^{N} E\left(e_k \mid x_i, \left\{a_{ij}^{r}\right\}, \Omega^{\ell}\right)$$

$$= \mu_k^{\ell} + \frac{1}{N} \sum_{i=1}^{N} a_{ki}^{r} \Gamma_k^{\ell} \left[\Gamma^{\ell}(\alpha_i) + \Gamma_0^{\ell}\right]^{-1} \left(x_i - \mu^{\ell}(\alpha_i) - \mu_0^{\ell}\right)$$

- **Class covariance update**

$$\Gamma_k^{\ell+1} = \frac{1}{N} \sum_{i=1}^{N} \operatorname{cov}\left(e_k \mid x_i, \Omega^{\ell}\right) + \left[E\left(e_k \mid x_i, \Omega^{\ell}\right) - \mu_k^{\ell+1}\right]\left[E\left(e_k \mid x_i, \Omega^{\ell}\right) - \mu_k^{\ell+1}\right]^{t}$$

- **Parameter updates are averages over expected values that are calculable from current parameters and abundance values**

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- **Hyperspectral Imaging (HSI) aka Imaging Spectrometry**
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  - Generalization of common models
  - Estimation
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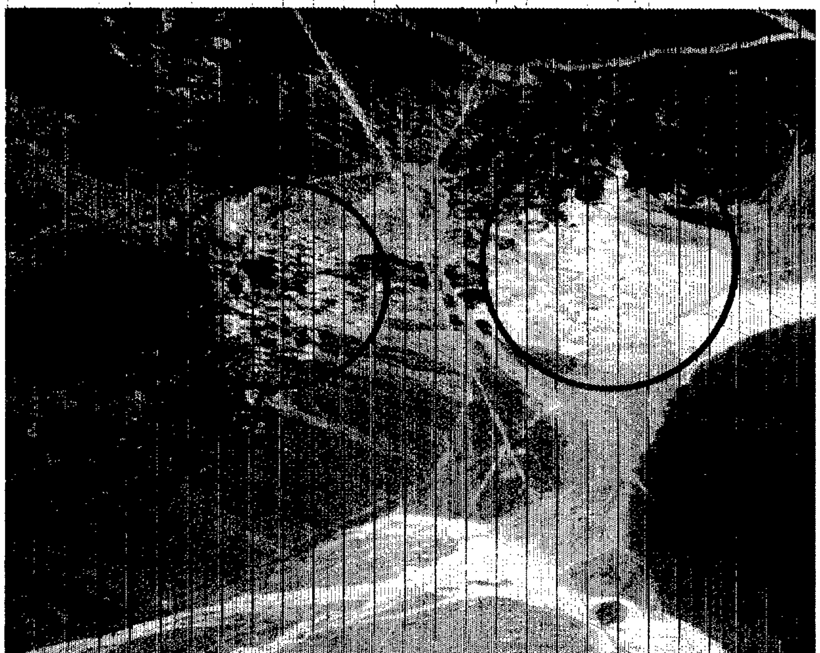
AVIRIS Imagery of Cuprite, Nevada

AVIRIS: RGB Cuprite, NV



Acid sulfate hydrothermal alteration centers created 7.6-6.2 million years ago (hot sulfuric acid laden water flowing through surrounding rock changes the mineral content)

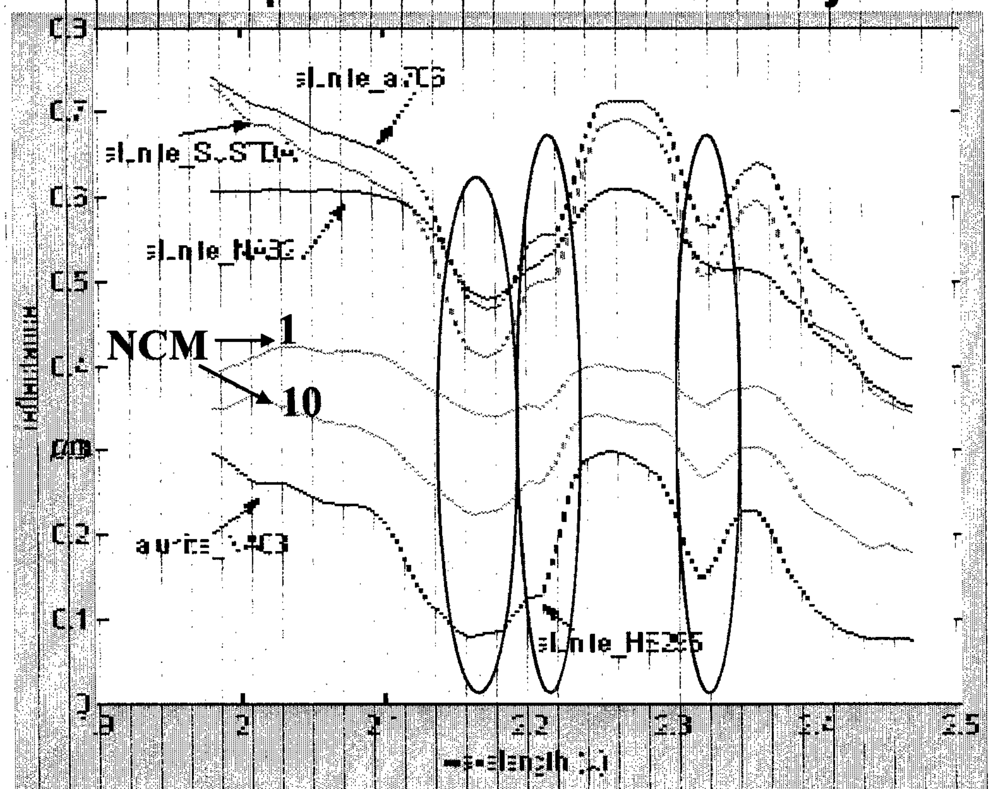
- Complex well studied scene used for evaluating algorithms
  - Mineral classification maps and spectral library available from US Geological Survey
  - USGS airborne hyperspectral identifications confirmed using ground spectrometry and laboratory analysis of field samples
  - 19 minerals plus 4 mixtures identifiable using SWIR data over 189 km^2 area
  - Subtle shifts in signatures due to variations in constituent elements, crystalline structure, temperature of formation
- Validate NCM estimation and blind unmixing
  - Sensor: AVIRIS
  - Spectral region: 50 bands (2-2.5μm)
  - Area covered: 42 km^2, 350 by 300 pixels extracted from a 189 km^2 image
  - Initial number of classes: 18

Identification of Spectra: Matching Absorption Features

- Alunite Group:
  $(Na,K)Al_3(SO_4)_2(OH)_6$

- Absorption Features:
  - 2.17 μ : Al-O-H fundamental
    - Higher formation temperature implies deeper and wider toward short end
  - Shoulder: O-H stretch+Al-O-H bend
    - Increasing concentration of Na shifts shoulder longer, and main band narrows
  - 2.31μ : O-H stretch+Al-O-H bend

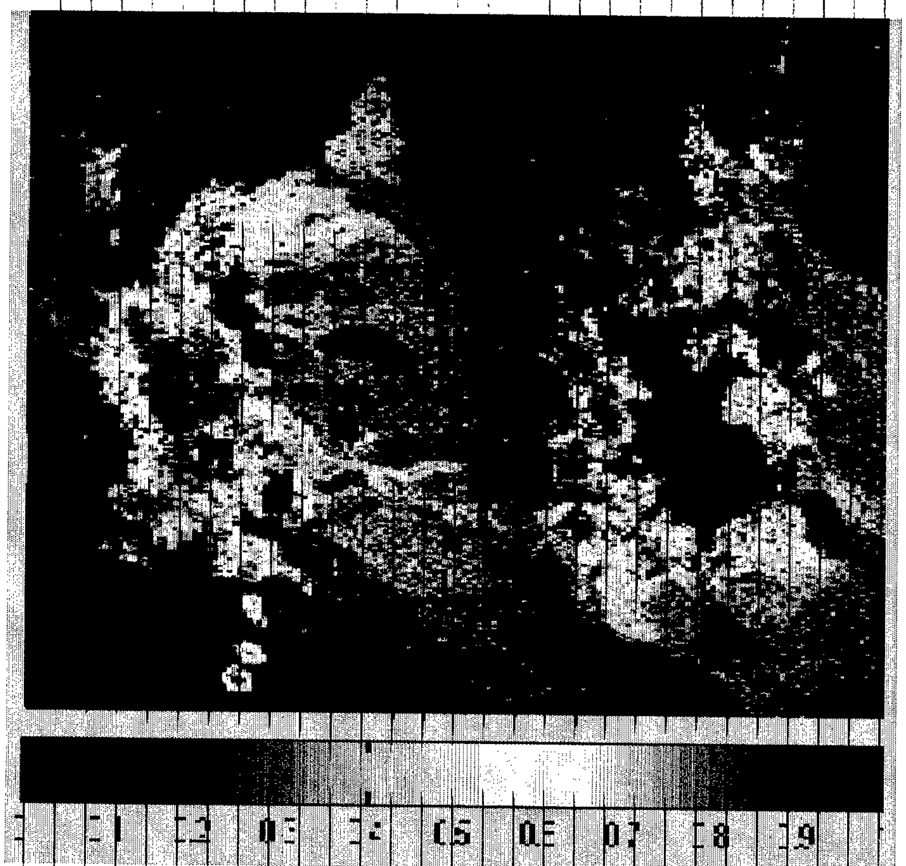
Alunite Spectra from USGS Library



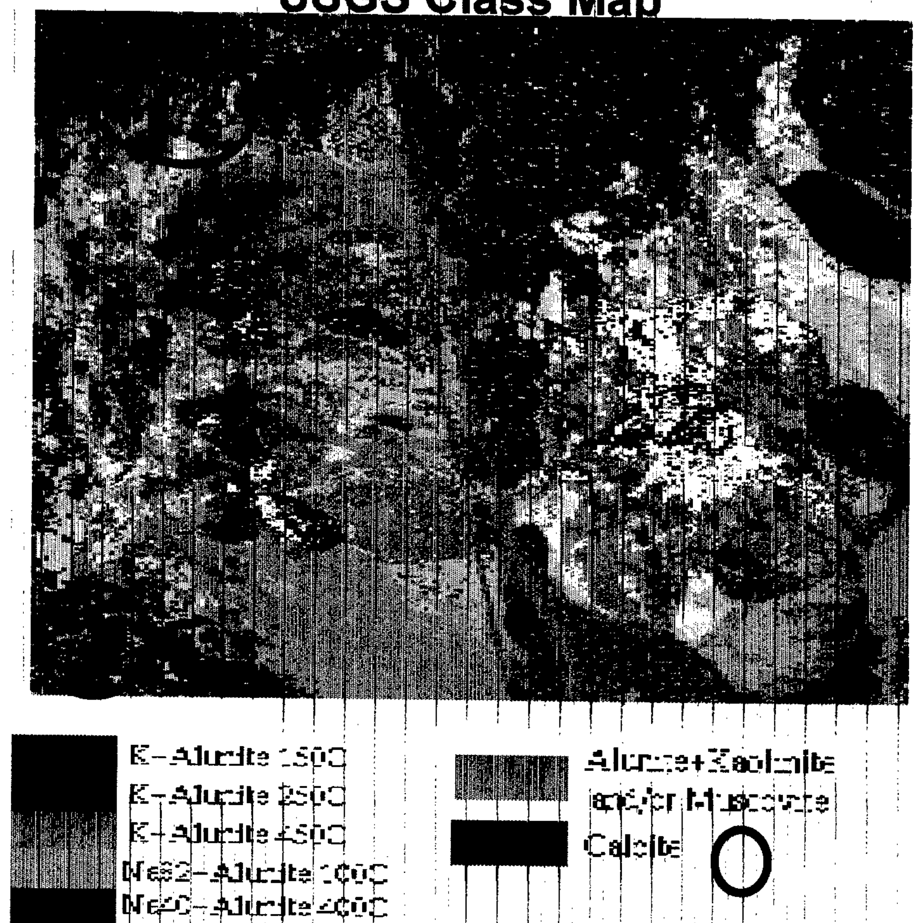
- NCM mean spectra identified with high temperature K-alunite (10) and moderate temperature mixed alunite (1) using USGS feature matching technique (correlation coefficients 0.99 and 0.98, respectively)

USGS Class Map and NCM Alunite Abundance Plane

NCM abundance: sum of classes 1&10



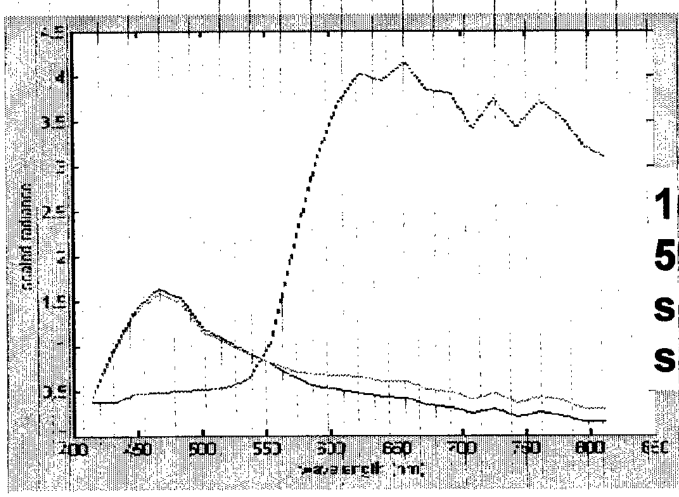
USGS Class Map



- Good qualitative comparison/ feature identification supports NCM unmixing
- Of 18 classes, 11 identified with minerals, 3 mixtures, 4 Fe bearing minerals

Detection Experiment: Life Vests in Ocean HSI

- Compare detection performance of Gaussian mixture, linear mixture, and NCM based known target and anomaly detection algorithms
- Background Data
  - 125-by-125 2 m^2 pixels
  - 24 band VNIR HSI (415-830 nm) from LASH sensor
- Target description
  - Life vest signature combined with background data from 1000 randomly selected pixels at 5% pixel fill fraction
  - 1 target class (mean given, covariance estimated as noise covariance)
- Model Parameters
  - 5 background classes



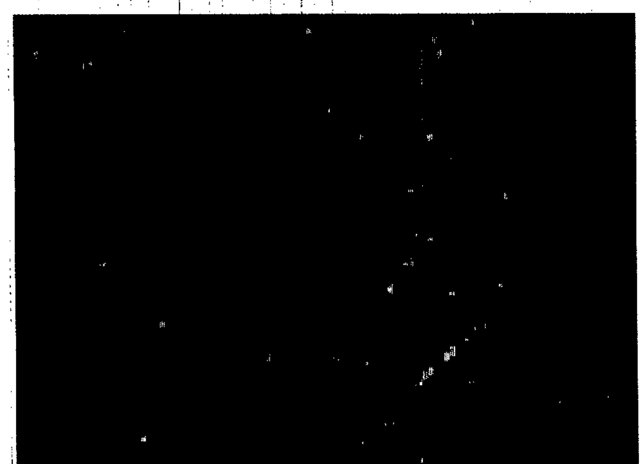
Signatures

100 % life vest

5% life vest + 95% scene mean

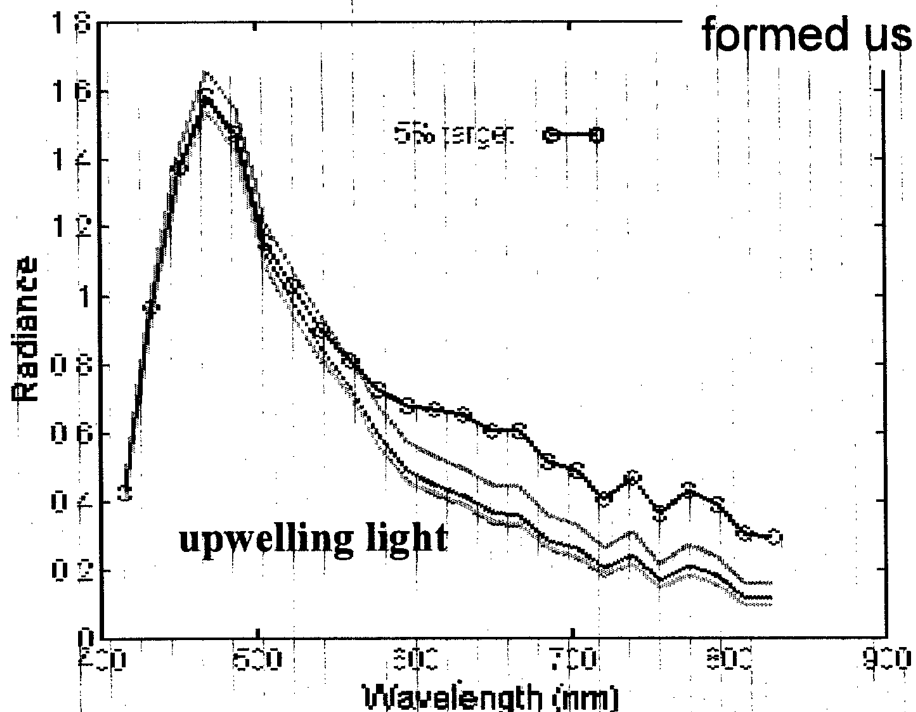
scene mean

Scene RGB



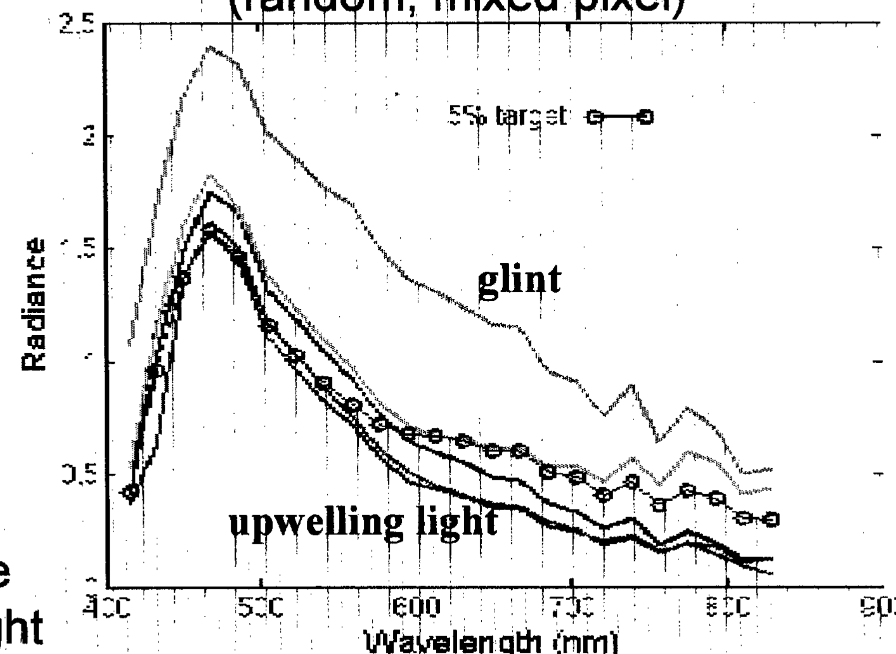
Mean Class Spectra: Normal Mixture and Normal Compositional Models

Normal Mixture Model
(random, pure pixel)



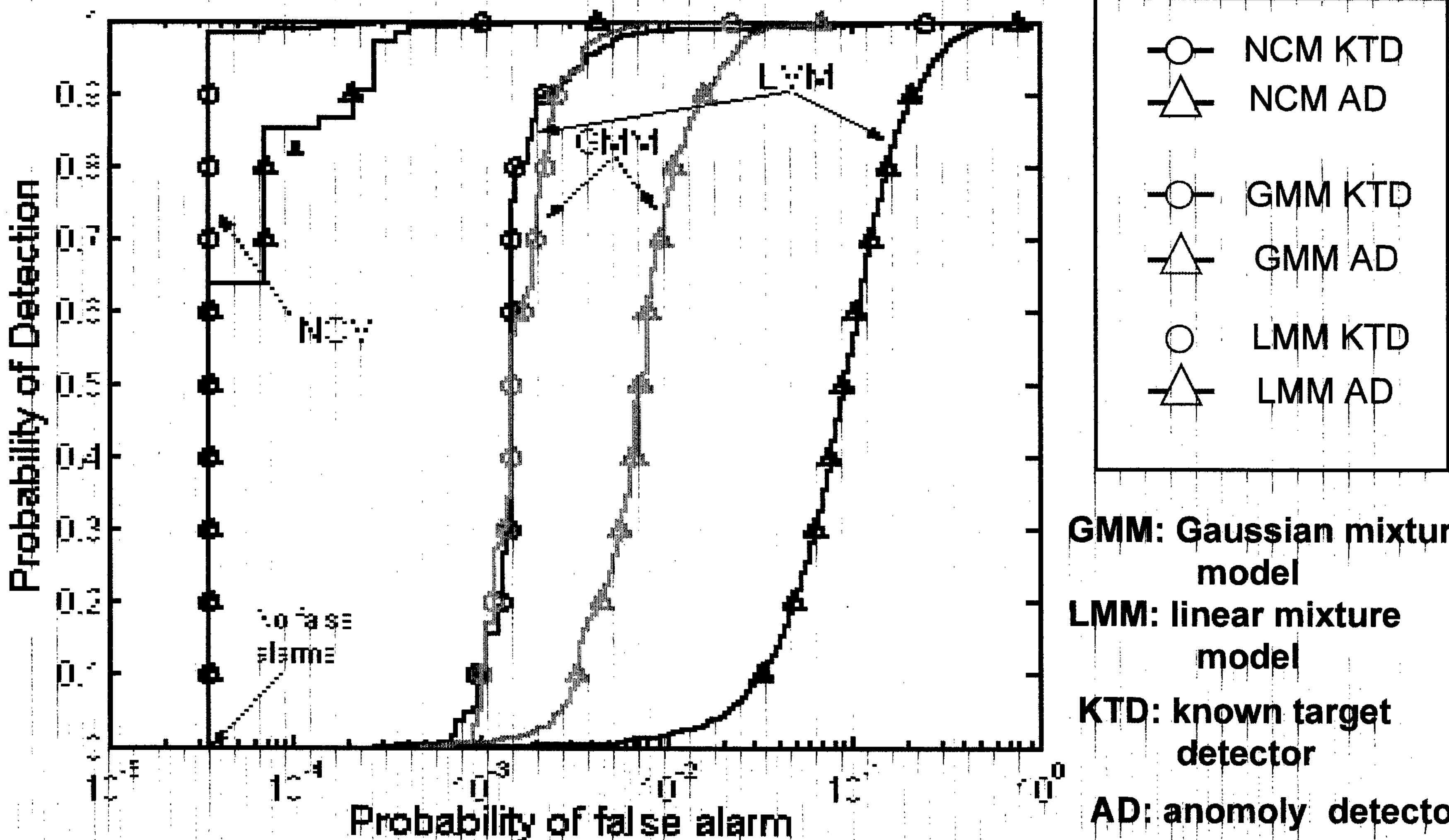
No distinct sea-surface reflection class formed using the normal mixture model

Normal compositional model
(random, mixed pixel)



NCM separates sea surface reflections and upwelling light

Comparative Detection Performance



GMM: Gaussian mixture model

LMM: linear mixture model

KTD: known target detector

AD: anomoly detector

Summary and Conclusions

- Described a normal compositional model (NCM)
  - simultaneously treats mixed pixels and intra-class variability
  - accommodates subspace, convex, and random class variability models
  - generalizes and synthesizes normal mixture, linear mixture, and subspace models
- Applied NCM to Cuprite data
  - Class means identified with spectra of materials in scene
  - Abundance estimates qualitatively corresponded with USGS classification maps
- Application to ocean data
  - NCM estimation method identified classes where pure-pixel methods failed
  - NCM offered superior detection performance in comparison with LMM and GMM based models

Future Work

- Speed up the software
- Applications to real time HSI systems
- Applications to HSI performance models